A Smart Predictive Framework for System-Level Stormwater Management Optimization

ABSTRACT:

Stormwater management in urban areas faces many global challenges like climate change and urbanization. However, municipalities are highly dependent on human decisions at system-level to achieve catchment scale stormwater management goals. This study presents a global real-time control approach for sustainable and adaptive management of stormwater. A network of inter-connected devices are assumed to dynamically generate the required set-points for the system actuators at the remote control center where global optimization algorithms calculate real-time operational decision-making target values. These target values activate the local controllers to manipulate the spatially distributed detention basin's outlets that enables a smart catchment scale optimal control. A real world watershed with four outlets to a nearby watercourse is chosen to test the applicability and efficiency of the proposed dynamic control approach. Results show that the proposed autonomous control approach has the ability to enhance the global performance of the stormwater management system in terms of quality and quantity to balance the network flow dynamics and environmental demands, while reducing the potential for erosion of receiving water bodies. Climate change is specifically discussed as a challenge for the designed control framework. Although, the performance criteria are shown to be affected by the increased rainfall intensities compared to actual rainfall scenarios, the proposed methodology still improves the peak flow reduction and detention time of water, at global scale, up to 54% and 14 hours respectively under climate change conditions.

Keywords: *Detention basin, Global control, Water quality, Real-Time control, Peak flow*

1. Introduction

Sustainable urban development relies on the design of advanced urban planning systems among which stormwater management infrastructures can play an important role in facing the challenges posed by urbanization and climate change (CC). For example, historical data about urbanization of a peri-urban area in Swindon, United Kingdom, showed that an increase of impervious cover from 11% to 44% increased peak flows resulting from runoff in downstream areas by over 400% (Miller et al., 2014). Besides, extreme climatic events and growing population have increased the need to upgrade stormwater management systems; it is now essential for urban stormwater management systems to operate dynamically and adaptively. Despite advances in technology, global digitally-enabled environmental systems have rarely been investigated. Employing smart systems and advanced Internet of Things (IoT) techniques, municipalities are now able to retrofit traditional stormwater infrastructures with sensors, actuated control valves and dynamic gates to allow an adaptive performance for controlling urban stormwater runoff against the changing environment (Kerkez et al., 2016). This allows transferring the conventional infrastructures that are controlled statically (with a single or a series of actions whose settings are constant in time) to dynamic and adaptive infrastructures. This has led to the definition of smart stormwater systems that aggregate observed and predicted data over the watershed for real-time monitoring and control of urban stormwater. Figure 1 illustrates the mechanism of a globally-controlled smart stormwater management infrastructure. Various field-deployed sensors collect the observation data of water quantity and quality over the network to finally store them into the cloud database. In addition, meteorological forecasting data, historical precipitation data and also data on actual weather conditions will be transferred to the cloud where all data is maintained, backed-up and analyzed remotely for further distribution over the network when needed. A remote control center looks over the network to generate decision-making target values for the local actuators. This performs as the core of the system and every decision made imposes a global impact on the whole system. Integrating IoT devices into such a system provides an embedded technology that enables proper communication, sensing and interaction between the stormwater system assets to achieve some common goals (Zhang, 2019). All these operations should be managed using a system-level control strategy that incorporates system flow dynamics and environmental demands for sustainable management of urban stormwater infrastructures. Although literature on the control of stormwater generally considers some simple rules to identify what actions need to be taken at the outlet of a drainage network to mitigate the impacts of urbanization on the natural streams (e.g. Gaborit et al., 2012), employing optimization algorithms proved to bring an enhanced performance for quantity and quality control of stormwater management systems. In a recently published study by Shishegar et al. (2019), a smart predictive decision-making framework is presented for real-time control of stormwater management basin in such a way that an optimization algorithm is integrated with some control rules to enable optimal quality and quantity control performance for the detention basin. Although this approach showed a significant improvement in the peak-flow reduction and detention time of the basin, it serves the stormwater system at local-level, and the impact of erroneous rainfall predictions on the real performance of this approach was not evaluated.

Optimized performance of a single basin does not necessarily result in an optimal performance at system-level, it would therefore be beneficial to study the operations of stormwater management systems as a component of a greater whole (Shishegar, Duchesne, & Pelletier, 2018). In addition, erosion, as one of the direct impacts of urbanization on the natural hydrological regime, can be an important source of phosphorus in watersheds (Wong & Kerkez, 2016) and proper stormwater management strategies are required to reduce erosion (Ministry of the Environment, 2003). However, without considering a system-level control, stormwater management practices may lead to adverse impacts such as erosion of waterbodies (Hawley & Vietz, 2016). Hence, controlling the velocity of *global* discharges to limit erosion is a necessity. There are only a few studies that have investigated the global performance of urban drainage systems as a whole (Cembrano et al., 2004; Darsono & Labadie, 2007; Duchesne, Mailhot, & Villeneuve, 2003; Martin Pleau, Colas, Lavallee, Pelletier, & Bonin, 2005), most of which consider combined sewer systems. There is a lack of practical solutions to enhance the system-wide performance of built stormwater management infrastructures; a solution that provides the system with the ability to perform dynamically and predictively against the varying environmental conditions and helps define an optimal control strategy that satisfies changing socio-environmental needs. As for the impact of uncertainties linked to rainfall predictions on the performance of real-time stormwater control systems, they have only been taken into account, to the authors knowledge, by Vezzaro and Grum (2014) and yet for the control of combined sewer systems. Yet, analyzing the performance of RTC strategies in presence of uncertainties can provide a more realistic and reliable decision-making while allowing an effective study of the resiliency of stormwater management systems as the ability to “bounce back” from a failure to the normal condition (Hosseini, Barker, & Ramirez-Marquez, 2016)

Figure 1- Smart Stormwater Management at System-Level

The aim of this study is to develop a smart framework for global control and optimization of urban stormwater via long and short-term flow planning. Such framework should be capable of reducing the peak flows at the outlet of a stormwater management network while improving the detention time of the received runoff in all system detention basins over the watershed.

More specifically, the objectives of this paper are:

- To propose a global predictive dynamic control (GPDC) approach to enhance the quality and quantity control performance of a stormwater management system in real-time at the catchment scale.
- To discuss the global resiliency of the system in critical situations such as more intense rainfall events imposed by climate change.
- To identify challenges of the proposed global approach by evaluating the comparative performance of a real catchment case study under dynamic and static approaches.
- To analyze the erosion reduction ability of the proposed system-level approach compared to the static approach.
- To evaluate the impacts of uncertainties linked to rainfall predictions on the performance of the proposed control approach.

2. Methodology

A global predictive dynamic control optimization approach (GPDC) is developed that involves establishing the optimal operation of stormwater system regulators during rainfall periods and then incorporating some water quality control rules to detain runoff in the basin during dry periods. This approach is the expansion of the local integrated rule-based and optimization approach proposed in Shishegar et al. (2019), where local controllers generate the operational set-point for each single stormwater basin locally without considering the global system state. In the present study, the strength of optimization techniques allows establishing a global mathematical model based on the local one, to coordinate the discharges amongst spatially distributed detention basins across an urban watershed using real-time observed and forecasted precipitation data. The proposed methodology is first tested on a case study drainage area in Canada using a 2013 rainfall series observed from a rain gauge near the studied case from May to November, that includes 74 rainfall events. Secondly a modified rainfall series mimicking the expected climate in 2050 is used to evaluate the performance of the proposed control approach in presence of climate change. For this purpose, 15% are added to the selected rainfall series as recommended in Ouranos (2015). First, the employed prediction data in both scenarios (2013 year and climate change) are supposed to be perfect. The impacts that errors on rainfall predictions can have on the performance of the approach are afterwards investigated.

2.1. Integrated rule-based and optimization approach

The global predictive RTC approach, GPDC, is based on the integration of several control rules into an optimization model, which aims at minimizing peak flows to the receiving water body under several constraints while maximizing the detention time up to a predefined limit. This optimization model, described in section 2.1.1 below, is run in sequence with the control rules described in section 2.1.2 over predefined time intervals, in such a way that the dynamic optimization algorithm is active as long as the inflow to all basins is not zero. Once the dry period starts, the quality control rules become active to decide on the detention time of water in each basin. All planning intervals (control horizons) are part of a rolling horizon framework that allows the system parameters to be continuously updated based on the newly received data (Ziarnetzky, Mönch, & Uzsoy, 2018). A simulation model is used in all steps of the optimization framework to assess the future performance of the system as a function of predicted rainfall events by incorporating all hydrologic/hydraulic characteristics of the catchment. The time in a rolling horizon context is defined in discrete periods of equal length, which are called time steps. Outflow scheduling from each basin is then computed at each time step by running the simulation and optimization models successively at over the control horizons. The control horizon is the period over which the dynamic outflow scheduling is planned with respect to several physical and hydrological limitations. Figure 2 illustrates the planning process using the rolling horizon approach. This process is supposed to be continued over a long period of time, namely the planning horizon, which can be either finite or infinite depending on the studied problem nature.

For all investigations in this study, a 6-hour inter-event time is considered, as recommended in MDDEP (2008) for Quebec province, to separate the 2013 rainfall series into rainfall events and compute the performance criteria. Additionally, a 2-hour control horizon is considered to run the integrated rule-based and optimization algorithms including 24 time-steps of 5 minutes. Also, the prediction horizon is up to 48 hours with an infinite planning horizon that allows the designed algorithms to operate as long as required.

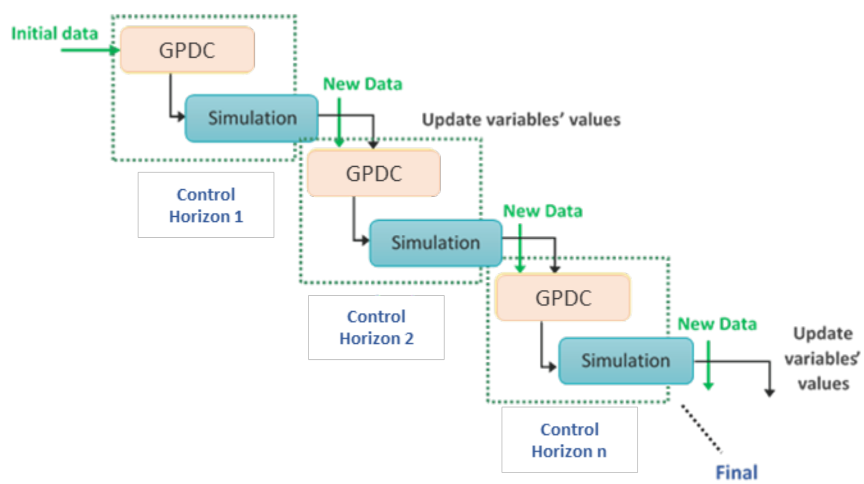

Figure 1-Planning by the Rolling Horizon approach and the Simulation-GPDC process

Figure 3 represents a stormwater network representation where the stormwater basins are considered as end-of-network storage structures connected to a smart controller with the ability to dynamically manipulate outflow rates while communicating with other controllers embedded over the network to balance the flow dynamics. This provides the stormwater system with the capabilities to not only measure, monitor and sense catchment parameters, but also to optimize the dynamic operations of these systems in an adaptive and predictive approach.

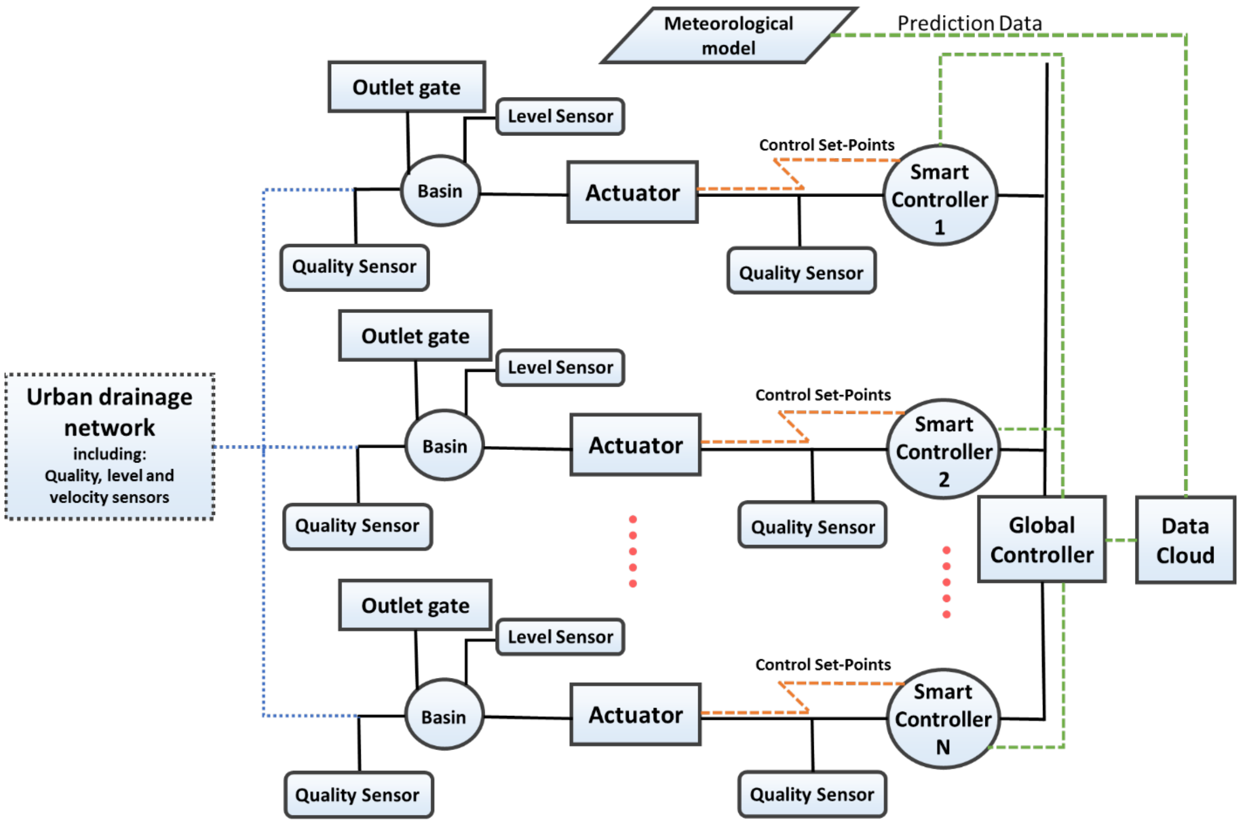

Figure 2-Schematic representation of a stormwater managemnt system and its associated assets

The N-basin network shown in Figure 3 concurrently directs urban runoff into the receiving watercourse via its detention basins. For this purpose, forecasting data must be available to support prediction-based decisions on stormwater detention basins, simulate the upcoming inflows and plan for the next rainfall events, while satisfying the settling process via quality control rules. All these decisions are made following the planning generated by the optimization model, which accordingly affects the interrelations between the basins even during the dry periods. This facilitates the stormwater system control so that its components operate jointly, while considering the overall state of the system. The quantity and quality control mathematical formulations will be explained in the next sections.

2.1.1. Dynamic Predictive Quantity Control Optimization Problem (PQ-COP) for interactions between the stormwater basins

A mathematical model is formulated, PQ-COP, to optimize the interrelationship operations of various stormwater basins. This optimization model aims at minimizing the total peak flow discharged from the stormwater management system to the receiving river and can be formulated as the following linear programming minimum cost function problem:

$$Min\left\{\sum_{i}\sum_{t}(\mathrm{Q}_{i,t}+\xi * pp_{i,t}+\varphi * qq_{i,t})\right\}$$

Subject to:

$$\sum_{t}(I_{i,t}-\mathrm{Q}_{i,t})\Delta t+V_{i,0}\leq V_{i,max} \quad \forall i=1,2,\ldots,N$$

$$Q_{i,t}\Delta t+2V_{i,t}=I_{i,t}\Delta t+I_{i,t-1}\Delta t+2V_{i,t-1}-Q_{i,t-1}\Delta t \quad \forall t=0,1,\ldots,L \;\&\; \forall i=1,2,\ldots,N$$

$$\mathrm{V}_{i,t}\geq 0 \quad \forall t=0,1,\ldots,L \;\&\; \forall i=1,2,\ldots,N$$

$$0\leq Q_{i,t}\leq Q_{i,max} \quad \forall t=0,1,\ldots,L \;\&\; \forall i=1,2,\ldots,N$$

$$Q_{i,t}-Q_{i,t-1}=pp_{i,t}-qq_{i,t} \quad \forall t=0,1,\ldots,L \;\&\; \forall i=1,2,\ldots,N$$

$$pp_{i,t}\geq 0 \quad \forall t=0,1,\ldots,L \;\&\; \forall i=1,2,\ldots,N$$

$$qq_{i,t}\geq 0 \quad \forall t=0,1,\ldots,L \;\&\; \forall i=1,2,\ldots,N$$

Where:

$Q_{i,t}$= outflow (decision variable) from basin i at time step t (m^3/s);
$pp_{i,t}$= negative variation of the set-point (continuous variable) associated to basin i;
$qq_{i,t}$= positive variation of the set-point (continuous variable) associated to the basin i;
ξ= weight associated to the positive variation $pp_{i,t}$;
φ= weight associated with the negative variation $qq_{i,t}$;
L= number of time steps in the control horizon;
$I_{i,t}$= inflow to basin i at time step t (m^3/s);
$V_{i,t}$= volume of water in the basin i at time step t (m^3);
$V_{i,max}$= maximum volume capacity of basin i (m^3);
Δt = difference of t between two time steps (s);
$V_{i,0}$= initial volume of water in basin i (m^3);
$Q_{i,max}$= maximum allowable outflow from basin i (m^3/s); and
N= number of controlled basins in the drainage network.

The linear decision-making model incorporates the simulated inflows to each storage basin to further generate the final optimal set-points related to the outflows from each basin. When applied in real time, the inflows, $I_{i,t}$, are computed from rainfall predictions using a hydrological/hydraulic model. The objective function is formulated in such a way that it provides minimum total outflow rates to the receiving stream during the control horizon.

2.1.2. Dynamic Predictive Quality Control Rules (DP-QCR) formulation

The pseudo-code of the proposed dynamic global predictive-quality control rules (DP-QCR) is presented below. These rules have been extended to a watershed with multiple stormwater basin systems from the quality control rules developed in Shishegar et al. (2019) for one single basin network. Here, at each time-step, based on the predicted precipitation data, the outflows from each basin are computed to decide on a proper detention time with respect to the defined constraints where:

$V_{i,req}$: required storage volume for the next coming rainfall event to avoid any overflow from basin i (m^3);

$t_{i,e} = \frac{V_{i,req}}{Q_{i,max}}$ = emptying time of basin i until availability of the required storage volume $V_{i,req}$ at maximum outflow $Q_{i,max}$ (s);

$t_{next\ rain}$ = time until the next predicted storm event starts (s);

t_f = time when the previous rainfall event finished (s);

t_i = emptying time of basin i at rate $Q_{i,t}$;

$t_{i,e}^{max}$ = emptying time of basin i until $V_i = 0$ at maximum outflow rate $Q_{i,max}$ (s); and

$V_{i,available}$ = available storage capacity in basin i (m^3).

The DP-QCR pseudo-code is as below:

```
Set the parameters of DP-QCR
for i=1:N
     set t_{i,e} = V_{i,available} / Q_{i,max}
          if t_{next rain} < t_{i,e} + t then
                    Q_{i,t} = Q_{i,max}
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if $t_{i,e} + t < t_{next\ rain} < t_{i,e} + t + 20h$ then
        $Q_{i,t} = Q_{i,max} * \frac{t_{i,e}}{t_{next\ rain} - t_f}$
if $t_{i,e} + 20h + t < t_{next\ rain} < t_{i,e}^{max} + 40h + t$ then
        $Q_{i,t} = Q_{i,max} * \frac{t_{i,e} + 20h}{t_{next\ rain} - t_f}$
if $t_{next\ rain} \geq t_{i,e}^{max} + 40h + t$ then
        if $0h \leq t_{i,e} \leq 40\text{h}$ then
            $Q_{i,t} = 0$
        if $40h < t_{i,e} < t_{i,e}^{max} + 40h$ then
            $Q_{i,t} = Q_{i,max} * \frac{t_{i,e} + 20h}{t_{i,e}^{max}}$
if $t_{next\ rain} - t_i > t_{i+1,e}$ then
    $t = t + t_i$
set i=i+1
```

After checking the last designed rule, this pseudo-code will be repeated for the next stormwater basin (N times in total) in order to set a proper detention time, by looking at $\boldsymbol{t_{next\,rain}}$ and the emptying time of the basin ($\boldsymbol{t_{i+1,e}}$). This allows the discharging process from the basins to be set either sequentially or simultaneously, depending upon the $t_{next\ rain} - t_i > t_{i+1,e}$ condition.

2.2. Erosion analysis

In this study, in order to evaluate the reduction of potential erosion, the Manning equation is applied to evaluate the velocity of storm flow discharges into the water bodies when the global predictive dynamic control strategy is employed. This approach that has been widely used in water engineering studies, is reported as an accurate formulation for water velocity analysis in operational hydraulics (Brutsaert, 2005).

2.3. Impact of errors on rainfall predictions

As mentioned before, perfect prediction data are first used to investigate the performance of the proposed control approach. Then, the impact of uncertainties linked to rainfall predictions on the performance of the proposed control approach is investigated. For this evaluation, prediction precipitation data from the High Resolution Deterministic Prediction System (HRDPS) version 5.0 (Environment Canada, 2020) were used. This model is a set of nested forecast grids that generate 48-hour predictions of atmospheric elements, including precipitation, at 1-hour time step 4 times per day (Kehler, Hanesiak, Curry, Sills, & Taylor, 2016). Analysis of prediction data obtained by this model shows that the quality of generated data in terms of accuracy of prediction varies during the day (Perez-Bello, 2020). Sensitivity of the model to the uncertain input data can vary based upon these accuracy variations.

The impact of using imperfect prediction data as the input parameter for the proposed dynamic control approach is assessed over a one-month period (July 2017). For this assessment, as illustrated in Figure 4, the parameters values are updated based on the observed data of the current system state at the end of each control horizon, while the planning for the next time-steps is performed based on the prediction data from HRDPS. It is worth mentioning that this evaluation could not be performed with the 2013 rainfall series, since the HRDPS predictions were available only from May 2017 onwards.

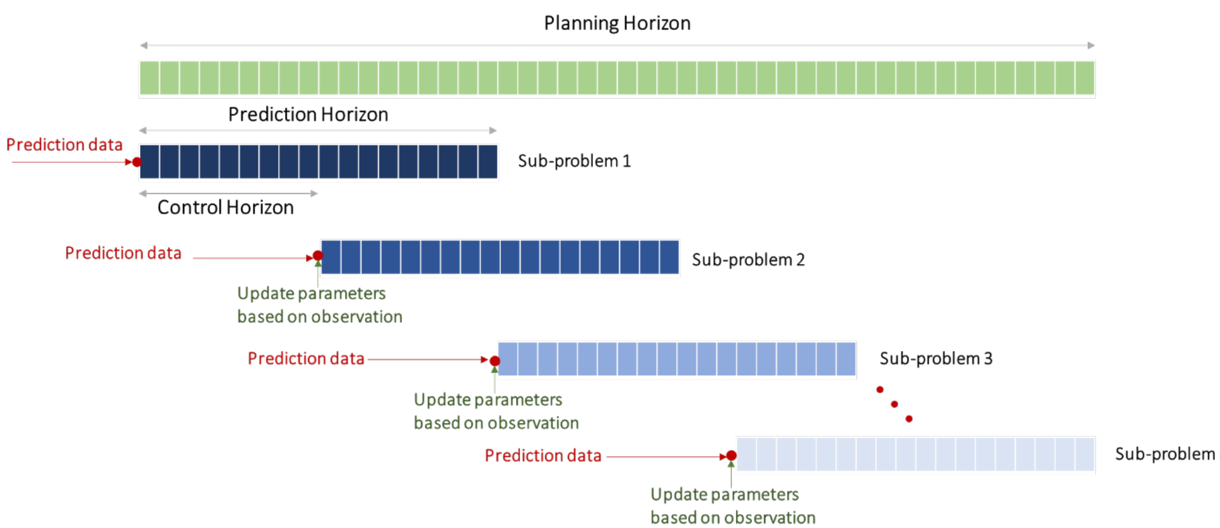

Figure 3- Assessment of the performance of the control approach when imperfect prediction data are used

2.4. Case study

The studied case is a Canadian drainage network located in a mid-size municipality in the province of Quebec, established on the banks of a river whose watershed covers an area of nearly 3400 km^2. This river is the main source of drinking water for the municipality, making the quality of its water crucially important, especially against the polluted urban runoff that annually discharges into this stream. The studied catchment is over 311 hectares, with erosion problems (mostly due to sharp peak flows) that increase the volume of sediments in the stormwater runoff which also carries relatively high levels of phosphorus, nitrogen and nitrites-nitrates due to industrial activities in the region (MDDEP, 2008). In addition, the sector is an urbanized and developed region that includes occupancy predominantly residential, with light businesses and some industrial, commercial and institutional lands, resulting in an average imperviousness of 55%. The hydraulic/hydrologic SWMM model (Rossman & Huber, 2016) of the drainage network has been provided by the municipality, which is the owner and manager of the sewer network. However, the network is currently a combined sewer network that is planned to be separated in the upcoming years. For the case study presented herein, in order to represent the behavior of the future stormwater network, all wastewater flows in the simulation model are valued as zero, to convert the combined sewer into a separate storm sewer model. Figure 5 schematically illustrates the studied sector, which consists of 470 sub-catchments, 526 nodes and 544 links. This sector is located in a denser part of the municipality and includes four outlets to the river (from left to right on Figure 5, A, B, C and D). Since the real drainage network is not separated yet, detention basins are not currently integrated in the network. For our case study, a detention basin was virtually added at each of the four outlets. These basins were designed using a 1-hr SEA design storm of 100-year return period, a maximum outlet discharge of 50 L/s/ha (based on municipal regulations) and a maximum height of 1.5 m, as detailed in the Supplementary Material section. The resulting characteristics of the four basins are summarized in Table 1.

Table 1-Charateristics of the drainage area and of the stormwater basins for the four studied outlets

Outlet	Drainage area (ha)	Maximum outflow rate	Orifice diameter (m)	Volume (m^3)
A	86.52	4.33 m^3/s	1.95	30430
B	80.53	4.03m^3/s	2.10	25670
C	115.67	5.78 m^3/s	1.80	18570
D	115.68	5.78 m^3/s	1.95	22160

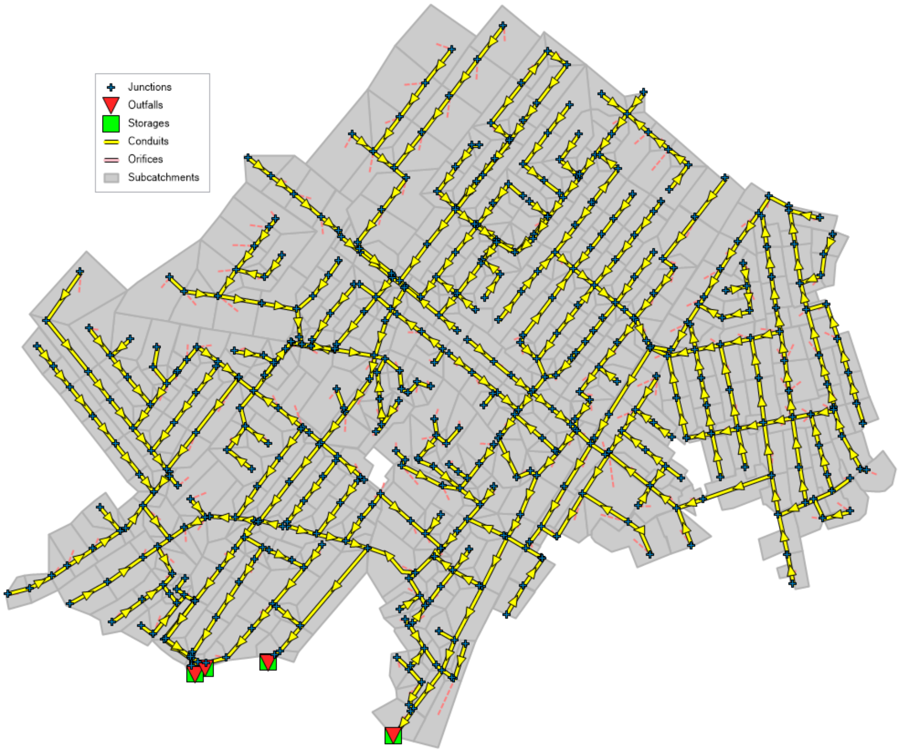

Figure 4- Simulation model of the studied sector using SWMM

2.5. Performance Criteria

In order to quantitatively evaluate the performance of the developed global control model, some performance indicators are extended based on the local RTC strategy performance criteria introduced in Shishegar et al. (2019) as presented below:

Peak discharge mitigation indicator that represents the peak flow reduction of the proposed dynamic control in comparison to the static control approach.

$$\rho_{i,r} = \frac{\mathrm{Q}_{i,r,max_{\text{static strategy}}} - \mathrm{Q}_{i,r,max_{\text{GPDC strategy}}}}{\mathrm{Q}_{i,r,max_{\text{static strategy}}}} \times 100$$

Equation 1

Where:

$\mathrm{Q}_{i,r,max_{\text{static strategy}}}$ = peak flow generated by the static strategy for basin i during rainfall event r.

$\mathrm{Q}_{i,r,max_{\text{GPDC strategy}}}$ = peak flow generated by the GPDC strategy for basin i during rainfall event r.

I. Quality control enhanced performance, that can be assessed through the detention time assigned by the dynamic model to each basin t_i^d.

II. Overflow prevention indicator formulated based on the percentage of volume capacity used within each basin $V_{t,i}^{ovf}$

$$V_{t,i}^{ovf} = \frac{\mathrm{V}_{i,t}}{\mathrm{V}_{i,max}} \times 100$$

Equation 2

III. Outflow variation minimization that is formulated based on the average outflow variation percentage and the number of variations ($\overline{Q_i^{var}}$ and N_i^{var})

$$Q_{i,t}^{var} = \frac{\left|Q_{i,t_{\text{GPDC strategy}}} - Q_{i,t+1_{\text{GPDC strategy}}}\right|}{Q_{i,t_{\text{GPDC strategy}}}} \times 100$$

Equation 3

Where:

$Q_{i,t}^{var}$: The variation of outflow at time t (t is in wet period)

It is worthy to note that the static control approach means that the outlet gate for each basin remains at a fixed position.

3. Results and Discussion

3.1. Peak flows and detention times

The overall results of the performance of the GPDC strategy for the entire studied watershed are provided in Table 2, assuming perfect predicted rainfall data, for the 2013 rainfall series and for the climate change scenario (2013 series increased by 15%). These results show that the mean peak flows from each basin are reduced by at least 75% and 57% for each scenario, respectively. Also, employing the dynamic control strategy caused a total mean peak discharge mitigation, over the static control strategy, of 59% for the 2013 rainfall series and 54% in presence of climate change. On the other hand, detention times demonstrate an improvement in the quality control performance of the proposed approach, with at least 17 h and 14 h mean detention times for all the 2013 rainfall events under actual and climate change scenarios, respectively. In addition, for the overflow control criteria, it can be noticed that despite realizing an enhance quality and peak discharge control performance, the risk of overflow is managed properly by not allowing the water volume to surpass the volume capacity of the basins. The highest average capacity used in both scenarios is related to the smallest basin, C, with 16% and 18% mean capacity usage under the actual and climate change scenarios, respectively.

Table 2-Performance criteria calculations for two scenarios and four studied stormwater basins over a year

Performance criteria (Mean ± Standard Deviation)	**2013 (actual) scenario assuming perfect predicted rainfall data**				
	A	**B**	**C**	**D**	**Total**
Peak discharge mitigation (%)	87 ± 47	77 ± 39	75 ± 40	78 ± 43	59 ± 38
Quality control (h)	26 ± 13	24 ± 14	17 ± 11	18 ± 13	
Overflow control (%)	8 ± 9	12 ± 11	16 ± 12	11 ± 9	
Mean flow variations	0.37	0.39	0.40	0.37	
Performance criteria (Mean ± Standard Deviation)	**Climate change scenario assuming perfect predicted rainfall data**				
	A	**B**	**C**	**D**	**Total**
Peak discharge mitigation (%)	68 ± 40	61 ± 39	58 ± 37	57 ± 40	54 ± 37
Quality control (h)	20 ± 11	18 ± 12	14 ± 9	14 ± 11	
Overflow control (%)	9 ± 9	11 ± 11	18 ± 15	13 ± 10	
Mean flow variations	0.38	0.43	0.42	0.39	

While the visual representation of the generated outflow schedule by the dynamic and static control approaches for the entire year of 2013 is difficult to illustrate, a clearer hydrograph can be provided for individual rainfall events. In this regard, the outflow schedules at the four studied outlets planned under the global predictive and static control approaches are shown in Figures 6 and 7 for the periods between June 10 and June 14 (actual scenario) and May 24 and 26 (climate change scenario), respectively.

As illustrated in Figure 6, the outlet gates are partially opened in sequence and not simultaneously to allow reducing the total peak discharge to the river. This contributes to the operation of the whole system where, by looking at the predicted meteorological conditions, the water flow variabilities are controlled efficiently at system-level. Besides, the generated schedule allows the settling process to improve the quality of released water by planning 10 h, 8 h, 14 h and 7 h of detention times for basins B, D, A and C respectively, while reducing the total peak flow rate by 68%.

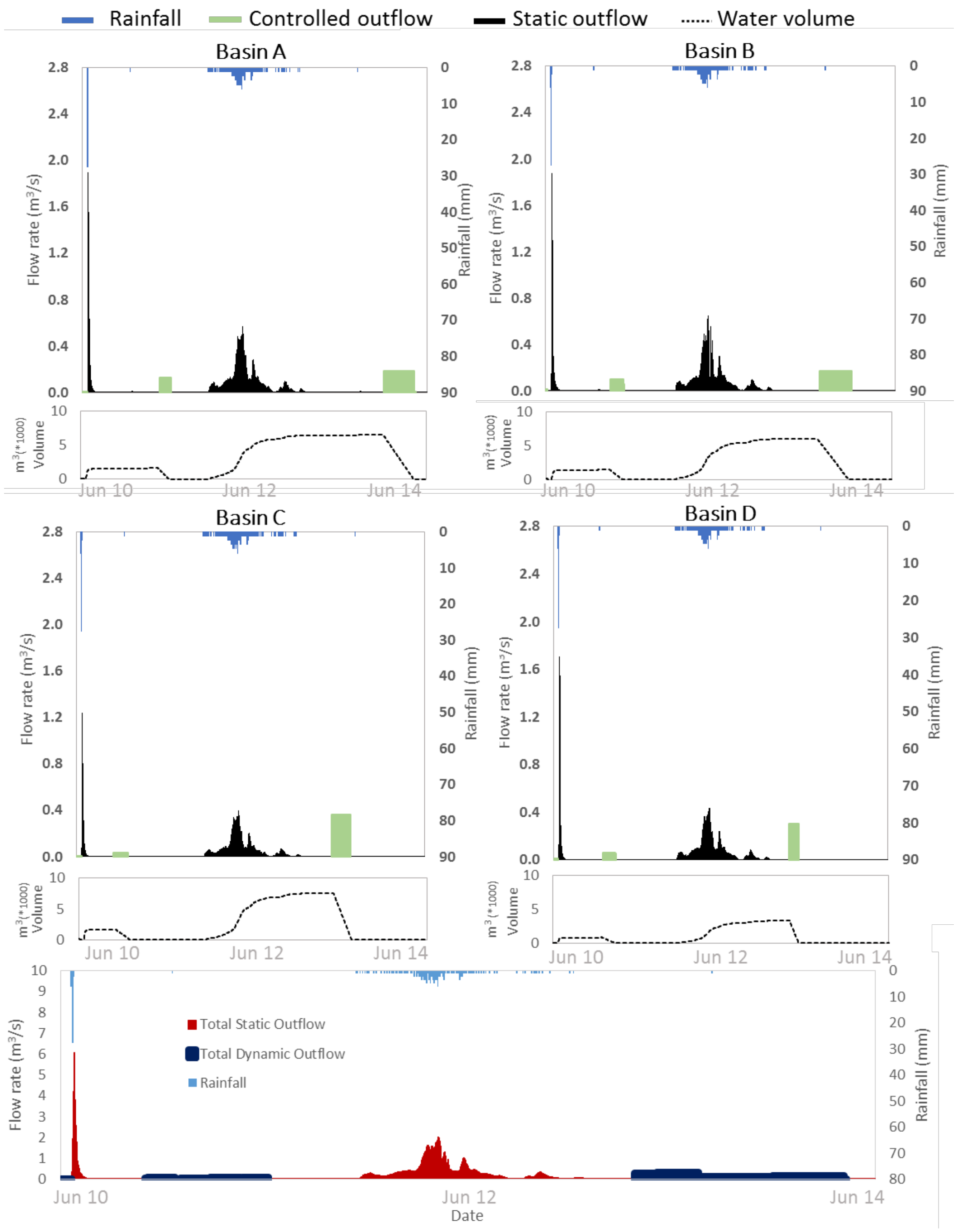

Figure 5- Outflow schedule under the 2013 rainfall series for the four studied outlets during a 4-day period (June 10 to June 14)

Figure 7 illustrates the results under the climate change scenario for a 3-day period after a critical and long storm event. As shown, the optimization aimed to reduce total outflows as much as possible to avoid any sharp peak flow in the river. This caused the water volume in the stormwater basins to reach a high level (the maximum level for the basin C) at the end of this rainfall event. Here, the GPDC framework assigns a relatively high outflow rate adjusted for each outlet, to minimize the overflow risk due to upcoming inflow to the basins. Hence, in such challenging circumstances, not only the safety of detention basins can be preserved, but the quality requirements of the runoff outflows can also be met.

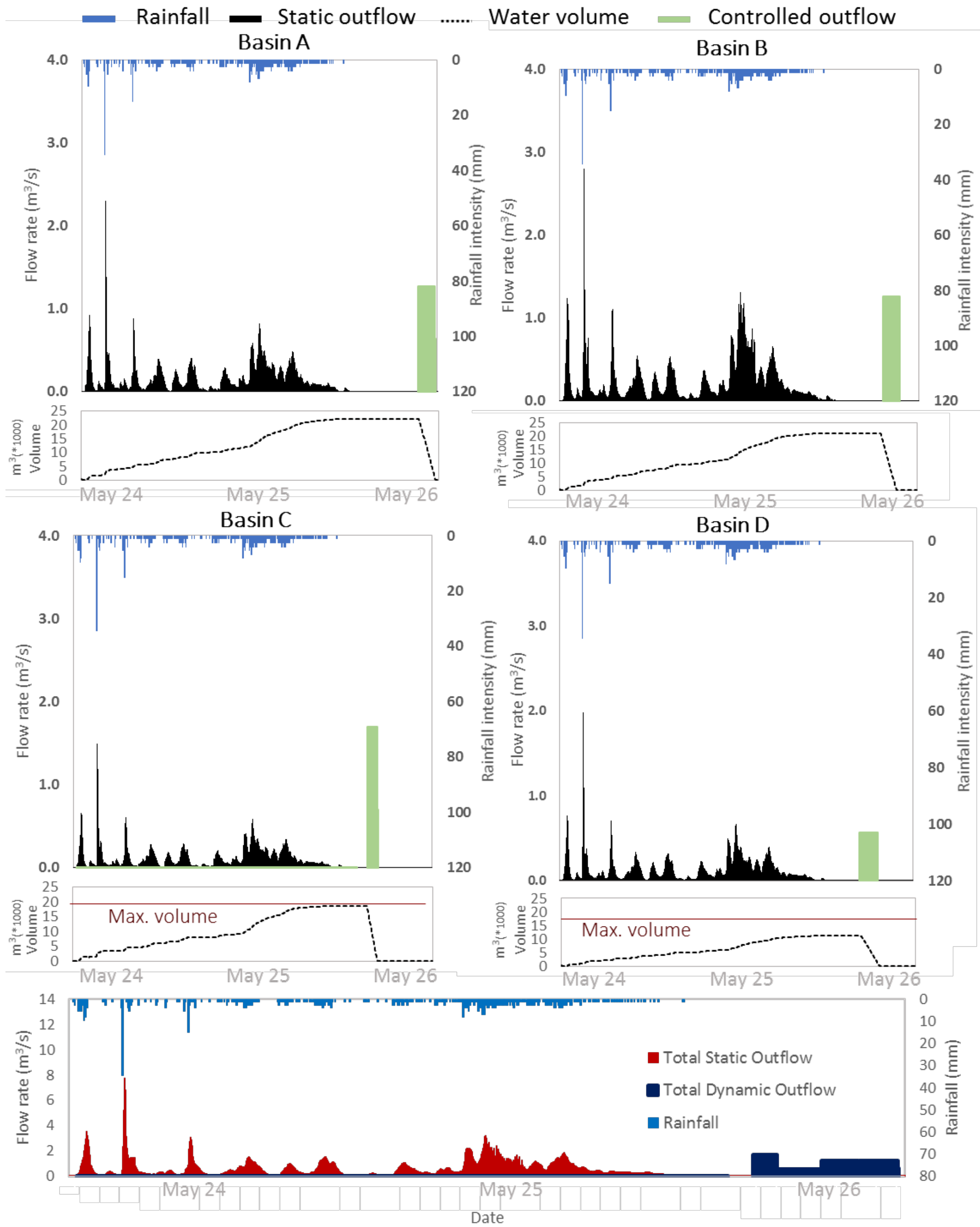

Figure 6-Outflow schedule under climate change scenario for the four studied outlets during a 3-day period (May 24 to May 26)

3.2. Erosion analysis

Table 3 shows the quantitative results obtained for both the static and dynamic control approaches. As expected, outflow velocities from the dynamic control approach are lower than those of the static control approach. Among the four studied outlets, B discharges the water slower than the others, probably due to the gentler slope of its outlet pipe (0.005 m/m). Conversely, C outlet produced more speedy outflows in comparison to the other studied outlets. Besides, the outlet pipes of the basins C and A have steep slopes to the nearby stream (the slope of C is almost 10 times larger than B) which contributes to the high outlet velocities.

Table 3-Studied outlets characteristics and velocity calculations

Outlet	**Slope**	**Velocity** (Mean ± Standard Deviation)		**Mean velocity reduction**
		Static	**Dynamic**	
A	0.04242	0.32 ± 0.19	0.15 ± 0.15	54%
B	0.00564	0.21 ± 0.13	0.10 ± 0.09	51%
C	0.05185	0.49 ± 0.31	0.33 ± 0.30	33%
D	0.02645	0.49 ± 0.29	0.30 ± 0.27	39%
Total				**47%**

The above-mentioned percentage reductions accounts for the efficiency of the proposed dynamic control approach in reducing the potential erosion imposed on the receiving waterbody.

Figure 8 shows 5-minute flow velocities at the B outlet for a 3-week period under climate change. The outlet velocity is the main parameter impacting erosive potential. It can be seen on Figure 8 that the dynamic control approach considerably reduces the velocity at the outlet and, consequently, the potential erosion of nearby streambanks.

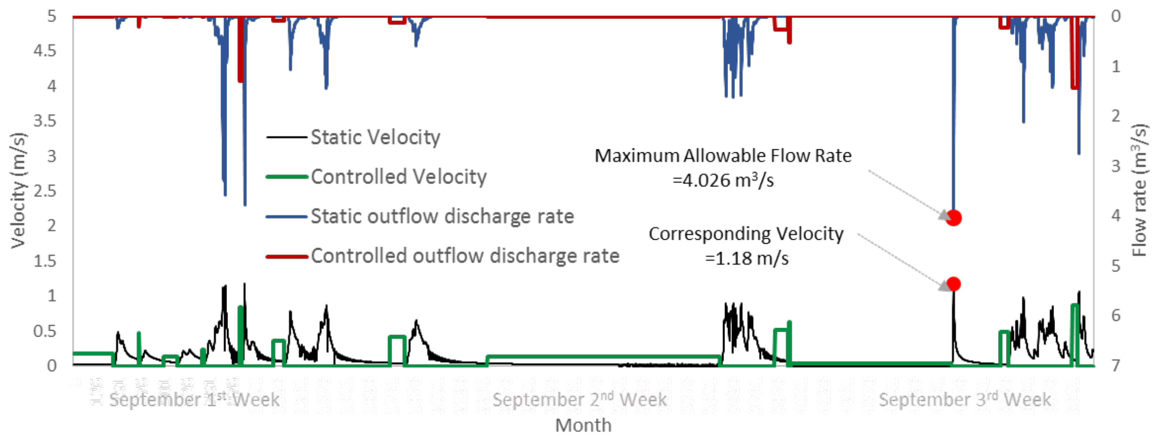

Figure 7-Flow velocity associated with the outflow rates produced by static and dynamic control strategies at B outlet under climate change scenario during a 3-week period

3.3. Impact of errors on rainfall predictions

Table 4 shows the calculated performance criteria as well as the number of overflows at each basin, computed when considering or not the errors on rainfall predictions. These results show that using the HRDPS prediction data as input to compute the control settings increases the risk of overflow and local flooding. Noteworthy, the higher peak discharge mitigation performance values shown in Table 4 in some cases, when errors in rainfall predictions are taken into account (like for basins A, C and D), does not necessarily mean that the model performed better. Rather, this could be due to not generating a proper response against an upcoming rainfall event and keeping the outlet closed, while it would have been a better strategy to open it to avoid any overflow. For example, in the case shown in Figure 9, although a zero outflow generated after a 20-mm rainfall event resulted in a higher value of the peak discharge mitigation performance criterion, it is followed by an overflow from the B basin.

Table 4-Quantitative comparison of the performance of the GPDC model when considering or not the errors on rainfall prediction data for July 2017

Performance criteria	Without considering errors on rainfall predictions					When considering errors on rainfall predictions				
	B	D	A	C	**Total**	B	D	A	C	**Total**
Mean peak discharge mitigation (%)	64	58	69	53	60	62	61	69	54	54
Mean quality control (h)	20	17	21	15	-	17	17	19	13	-

Mean overflow control (%)	12	15	12	16	-	15	19	14	22	-
Mean flow variations	0.32	0.29	0.32	0.36	-	0.29	0.26	0.29	0.32	-
No. of overflows	0	0	0	0	0	1	1	1	1	4

As an example, Figure 9 illustrates a critical situation where the prediction model is not properly able to forecast a 20-mm rainfall event may result in undesirable outcomes. Although the proposed dynamic model is designed in such a way that it receives the new data at each time step, the best currently available prediction models, like HRDPS, provide forecasting data significantly less frequently (at each 6 hours in the case of HRDPS). In this situation, given the variability of the weather condition, there is a possibility of not providing enough volume capacity for an upcoming extreme event because of not forecasting it well. Retarded discharge of stored water may result in basin overflow. As shown in Figure 9, an unpredicted rainfall event occurred while the basin was not prepared for the runoff caused by this rainfall episode. In this case, the integrated model decides to keep the water in the basin without being aware of the 20-mm coming rainfall. This causes an overflow from the basin, which is reported to the model in the next time step, when it generates the outflow set-points that allow discharging the water into the nearest stream. This shows that, although the rainfall predictions are not precise enough in this example to avoid any overflow, the dynamic performance of the GPDC framework enables a fast and reliable recovery of basin overflow caused by inaccurate prediction data.

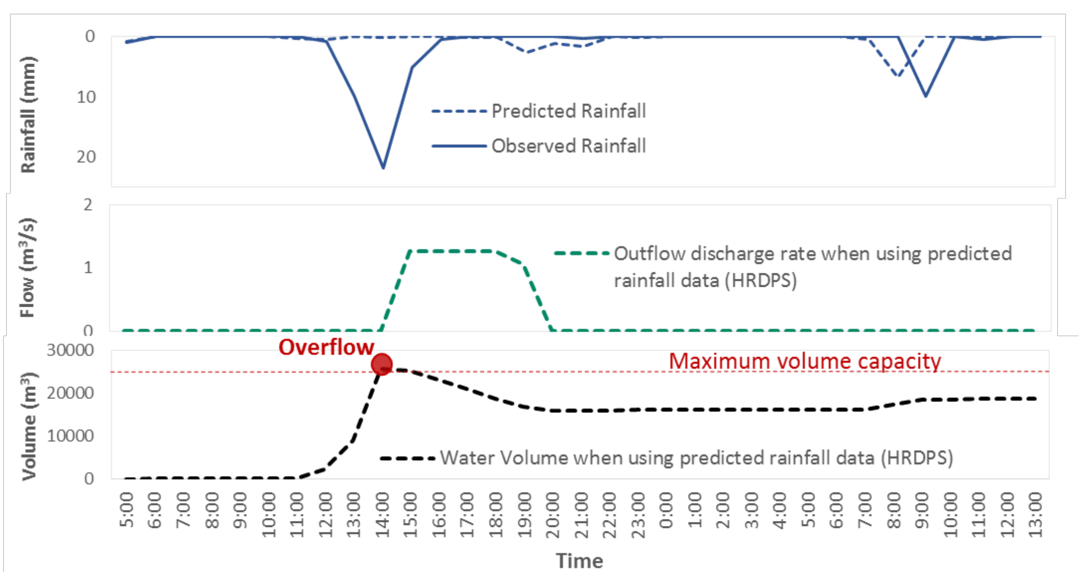

Figure 8- GPDC strategy performance when considering the errors in rainfall prediction data (a 20-mm rainfall event is not foreseen)

To sum up, these results demonstrate the importance of taking into account the uncertainty linked to input parameters and data when assessing the performance of a control approach. Although the performance of the GPDC strategy depends on the quality of the prediction data, it has the ability to recover when faced with unpredicted events and provide the system with a resilient decision-making process. Thus, future studies should focus on the system resiliency and features that could be added to the stormwater management infrastructures and/or control approach to act as a back-up in case of intense unpredicted events. However, it is suggested to address the resiliency measures based on multiple functionalities of the system as the focus on the enhanced resiliency of one system functionality may result in degradation of other functionality resilience (Shin et al., 2018). Another solution can be the robust optimization approach where the "best policy" is found by considering a variety of uncertain scenarios (Y. Jia & Culver, 2006). However, satisfaction of the worst-case scenario as the fundamental concept of a robust approach may impose excess cost on the specific objective function of the studied problem (like extra designed capacity for the basin that may never be used). Yet, a stochastic approach can consider different overflow probabilities to provide a reliable solution facing with rainfall uncertainties (Yazdi, Lee, & Kim, 2014).

4. Summary and Conclusion

A system-level predictive real-time control optimization and rule-based algorithm was introduced in this study as an adaptation measure to modernize traditional stormwater management systems considering new emerging global challenges. This algorithm performs as the core for a smart stormwater management system enabling the system components (like detention basins) to act inter-connectedly in order to balance the flow dynamics based on the meteorological variations. Both quality and quantity of water were considered in designing the dynamic control algorithms that provides an overall improved performance for the studied catchment. This provides a multi-disciplinary framework that attenuates the total peak flow to the stream, enhance the quality of water through sedimentation and reduce the erosion of receiving streambanks.

Results showed that the global quality and quantity performance of the system improved considerably when applying the proposed approach, with a 59% mean reduction in total peak flows and a 21h mean increase in average detention time, as compared to static control, when considering the observed rainfall series of year 2013. It was also shown that, with a modified rainfall series taking climate change into account, average peak outflow velocity using the dynamic control approach is reduced by 47% in comparison to the static control approach. Hence, the proposed global dynamic control approach provides an efficient tool for decision makers to prevent disruptive impacts of urban runoff on natural streams.

Integrating data-driven dynamic models in smart stormwater infrastructures can thus enable multiple system components to be adapted to environmental variabilities through process optimization and automation, and bring improved operational efficiency, better level of service and greater accountability for these systems. In presence of global challenges like climate change, urbanization and growing populations where the significant stress on urban infrastructures is undeniable, deployment of technology-based urban stormwater management infrastructure that is more environmentally friendly and resilient seems to be a necessity to improve social and environmental well-being. However, this inherent ability comes with some uncertainties when operating based on weather forecasting data. Results presented herein showed that, although the errors in predicted input parameters may cause miss-operation of the system, the dynamic nature of the predictive model helps the system to rapidly recover from failures like overflows. Hence the proposed methodology, in its actual form, can be used by decision makers to transform conventional infrastructures into smart and modern urban systems that performs dynamically against varying environmental conditions. However, as a further research direction, robust, stochastic and resilient-based approaches should be developed and tested, to provide more reliable solutions for the system. Since the frequency and intensity of extreme storm events is increasing due to climate change, integration of such approaches to distributed real-time control framework becomes even more essential in highly developed urban areas where there are tens, or even, hundreds of stormwater basins. By providing accurate spatio-temporal parameters of the system to the control mechanism in order to optimally shape the outflow hydrographs of these basins, we can preserve waterbodies from probable ecological damages, avoid excess sediment mobilization and finally provide an adaptive performance facing with emerging global challenges.

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5. SUPPLEMENTARY MATERIALS

Stormwater Basin Sizing Method

Currently, there is no detention basin at the four outlets of the studied case since the sewer network is still combined. A volume-based methodology was applied for sizing the four detention basins. For this purpose, an initial width for the detention basin and a diameter for the outlet orifice is set to further iterate the hydraulic/hydrologic simulation model and find the smallest combination of the outlet diameter and the basin width while respecting the two following design criteria: a) the maximum storage depth (1.5 m), and b) the maximum allowable outflow rate which is defined by the municipal regulations (50 L/s/ha). It should be noted that the designed basins have a truncated rectangular pyramid shape with a 4:1 length/width ratio. While a detention basin with a high length/width ratio is more effective in removing pollutants (Meyer, 1985), a report by Missouri Office of Administration (2008) shows that a 4:1 ratio is appropriate to capture fine sediments. Thus, this study considers a length-to-width ratio of 4:1 and slopes of horizontal to vertical ratio of 3:1. Furthermore, MDDEP (2008) recommends a variable height between 1 and 2 m for a detention basin. For this application, 1.5 m is considered as the maximum height of the stormwater basins.

A 1-hr SEA design storm of 100-year return period was used for the sizing of the basins. Using the data from the studied rain gage IDF curve (Agrométéo Québec, 2020), located in the same region as the case study, this leads to a total of 59.6 mm of rainfall distributed as illustrated in Figure S.1. The SEA rainfall distribution model has been originally developed based on real storm mass curves of southern Quebec and proved to be suitable for urban runoff calculations in this region (Ministere de Developpement durable & MAMROT, 2014).

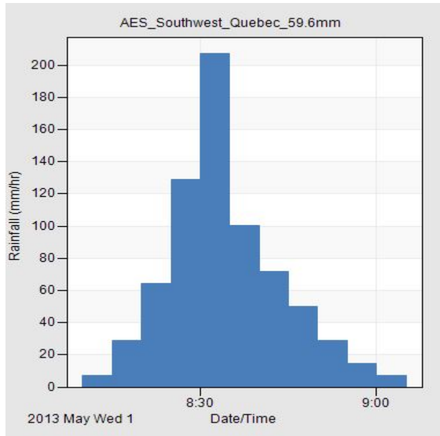

Figure S.1- SEA design storm used for sizing the four basins

Once all the preliminary calculations were done, the simulation model was adjusted through an iterative process until the required criteria (maximum height in the basin and maximum allowable flow at the outlet) were met with the smallest outlet orifice diameter and the smallest width possible for each basin. The resulting combination of the outlet diameter and the basin width with the calculated sizing for each basin is presented in Table 2.

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